A hybrid Prognostics Approach for Motorized Spindle-Tool Holder Remaining Useful Life Prediction

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Abstract The quality and efficiency of high-speed machining are restricted by the matching performance of the motorized spindle-tool holder. In high speed cutting process, the mating surface is subjected to alternating torque, repeated clamping wear and centrifugal force, which results in serious degradation of mating performance. Therefore, for the purpose of the optimum maintenance time, periodic evaluation and prediction of remaining useful life (RUL) should be carried out. Firstly, the mapping model between the current of the motorized spindle and matching performance was extracted, and the degradation characteristics of spindle-tool holder were emphatically analyzed. After the original current is de-noised by an adaptive threshold function, the extent of degradation was identified by the amplitudes of wavelet packet entropy. A hybrid prognostics combining Relevance Vector Machine (RVM) i.e AI-model with power regression i,e. statistical model was proposed to predict the RUL. Finally, the proposed scheme was verified based on a motorized spindle reliability test platform. The experimental results show that the current signal processing method based on wavelet packet and entropy can reflect the change of the degradation characteristics sensitively. Compared with other two similar models, the hybrid model proposed can accurately predict the RUL. This model is suitable for complex and high reliability equipment when Condition Monitoring (CM) data is scarcer.

Keywords Spindle-tool holder, Performance degradation, Remaining useful life, Relevance vector machine

1 Introduction

Advanced Computer Numerical Control (CNC) equipment has been widely applied in aviation, energy and automotive industries, of which are large-scale, expensive and highly precise. As a critical component of CNC equipment, high-speed motorized spindle has a considerable impact on material removal rate and surface quality. Motorized spindle-tool holder matching is one of the critical factors of the spindle system. Its performance and stability affect the accuracy and dynamic characteristics of the processing system directly. Due to the different machining conditions and production environments, the life of CNC equipment varies greatly. The maintenance strategy of periodic replacement of mechanical components is neither scientific nor reasonable. Most systems, especially mechanical systems, usually do not suddenly fail, but will undergo a gradual degradation process until failure occurs [1]. The system state before failure is monitored and predicted by intelligent model and logic algorithm based on the characteristic information collected by sensors, so as to determine the optimal maintenance time.

The RUL is the time when the degradation state of the equipment reaches the pre-set failure threshold from the current moment. RUL prediction approaches are divided into physics-based models, statistics-based models, artificial intelligence models (AI models) and hybrid models [2]. Physics-based models predict the RUL by solving a series of equations which define the dynamics and the degradation mechanisms of the system [3]. When the degradation mechanisms and correspondent equations are accurately identified, the physics-based models have the property of long-term behaviour [4] [5]. For motorized spindle-tool holder, the main failure modes include fatigue and wear. At the same time, the contact stiffness of spindle-tool holder has great influence on dynamic performance[6]. It is difficult to construct an accurate degradation model to characterize the RUL.

Statistics-based models assume that the RUL obeys some function distribution based on empirical data [7]. The RUL prediction model is established by fitting available observed data into random coefficient models with probabilistic method, which does not depend on any physics or mechanism principle. Compared with other models, the advantage of statistical analysis method lies in its nice mathematical properties for analyzing the RUL [8]. Data for RUL include event data and CM data. With the increase of reliability of motorized spindle, it is difficult to obtain enough event data of spindle-tool holder. CM data of motorized spindle include vibration data, current data, temperature data, etc. Statistical-based model can only characterize the general degradation characteristics of one type of equipment, but it can’t reflect individual differences [9]. The spindle-tool holder has the characteristics of multi-varieties and small batches. Even the same kind has a great difference in its machining conditions. Only statistical-based model can’t reflect temporal variability in RUL prediction [10].

With the development of sensor technology and acquisition technology, more and more CM data are available. Features (kurtosis, root mean square or entropy) are extracted from CM data (such as vibration, current and pressure), and degradation curve is constructed. The AI model is suitable for predicting the RUL of complex equipment which is difficult to construct physics-based model or statistical-based model. Typical prediction methods based on AI include artificial neural network, neuro-fuzzy systems, Support Vector Regression(SVR) /RVM , etc. Heng et al [11]. proposed a feed-forward neural network prediction method for pump vibration data, using the feedback layer of recurrent neural network to make it possible to the non-stationary state. Chen et al [12] used adaptive neuro-fuzzy inference system and high-order particle filter to predict machine state. At present, there is no unified standard to determine the hierarchical structure of neural networks, while the structure of neuro-fuzzy inference system depends upon expert knowledge and intelligent neural networks. Both them depend on massive and good- quality CM data.

Because the practical working conditions of spindle-tool holder are complex and changeable, the CM data under fixed working conditions is scarce, non-linear and dynamically uncertain. However, SVR and RVM are good at processing small sample data. Benkedjouh et al [13]. adopted two nonlinear feature reduction techniques (expectation-maximization for principal component analysis and isometric feature mapping) combined with SVR. The obtained nonlinear regressions are fitted to power models for predicting the RUL of the cutting tools. Hyper-parameters optimization of SVR was specially analyzed by Loutas [14]. The analysis shows that in order to avoid over-fitting, certain hyper parameters are defined empirically based on preliminary trials. Although SVR is widely used, it depends on the regulation of super parameters [15]. The kernel function must satisfy Mercer criterion. Compared with SVR, the kernel function of the RVM is not restricted by Mercer condition, and its parameter setting is simple [2]. Uncertainty factors of spindle-tool holder in high speed cutting include cutting force, centrifugal force and clamping force. RVM is more suitable for uncertain conditions compared with SVM [16]. It has better generalization ability. However, because it is difficult to understand the internal structure of AI models, such models are also called black box models.

The hybrid prediction is to integrate the above methods and make use of their respective advantages. The AI model was often combined with statistical-based model [17][18]. Firstly, an AI model can estimate the internal status of components when it can't be obtained directly from the sensor signal. After that, the estimated components state can be extrapolated to the threshold using statistical-based model. The final prediction accuracy depends on the fusion mechanism [19].

The elastic connection of the spindle-tool holder determines the dynamic characteristics of the spindle system. The von-Mises stress has non-liner distribution because of the clamping force of the holder and the centrifugal force caused a stress concentration [20]. In practice, the degradation of the spindle-tool holder can be different and incomplete significantly due to different cutting conditions. Based on the above factors, we explore a hybrid prediction model combining RVM (AI-model) and power regression (Statistical-based model) to predict the RUL of spindle-tool holder dynamically.

The remaining chapters of the paper are arranged as follows: Section 2 analyzes the current loss of motorized spindle and the failure mechanism of Hollow Taper Shank (HSK) spindle- tool holder. Section 3 presents extraction of performance degradation features. In section 4, a hybrid prognostics method model based on RVM is proposed. The proposed model is verified by experiments in section 5. Conclusions are discussed in section 6.

2 The Current loss of motorized spindle and failure mechanism of HSK spindle-tool holder

In the process of high speed machining, the motorized spindle is subjected to alternating torsion, repeated clamping wear and huge centrifugal force. After a certain period of time, fatigue damage occurs on the mating surfaces, which leads to changes in contact area, contact stress and contact stiffness, thus resulting in performance degradation in dynamic transmission, rotary accuracy and repetitive positioning accuracy[21][22].

2.1 Loss and consumption analysis of the current

The current consumption of motorized spindle is mainly divided into mechanical loss and electromagnetic loss. The mechanical loss mainly includes the loss of front and rear bearings, the loss of cutting force (including the loss caused by the change of performance at the mating of the spindle- tool holder) and the wind-friction loss of AC motor [22]. The electromagnetic loss mainly contains the iron core loss and copper winding loss of AC motor. The mechanical loss is shown in Fig. 1. T_c is the torque consumed by cutting force and the matching surface. T_{B1} and T_{B2} are the torques consumed by front and rear bearings duo to viscous friction force and Coulomb friction, respectively. T_A is the sum of the frictional torques between the outer surface of the rotor and the air, and between heat dissipating fan and the air.

The total current consumption of motorized spindle can be expressed by Equation (1):

$$I = K\omega(T_c + b_\omega + T_f) + I_m \tag{1}$$

where: K is the load-related coefficient, ω is spindle angular speed. b_ω is bearing viscous friction torque, T_f is bearing Coulomb friction torque, I_m is the current consumed by copper winding, iron core and wind resistance of stator and rotor.

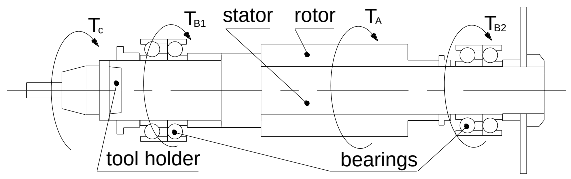

Fig.1. Mechanical loss of motorized spindle

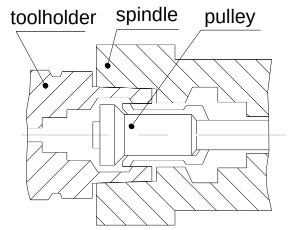

Fig. 2. HSK tool holder and spindle matching connection

2.2 Failure mechanism analysis of HSK spindle -tool holder

HSK tool holder is considered to be one of the most suitable forms for high speed cutting at present. It adopts the structure of 1/10 taper, hollow, thin wall and short taper. During machining, the HSK tool holder is fitted with the end face and the conical surface.

There are three main failure modes of mating surfaces [23] [24]:

(1) Failure due to insufficient strength

The complex structure of the HSK tool holder is easy to cause stress concentration. In high-speed cutting process, centrifugal force is far greater than cutting force, which becomes the main load. When the stress exceeds the yield limit, it causes plastic deformation of the mating surface, leading to cracks and even fracture.

(2) Joint failure

Due to the insufficient pulling force, it can't ensure that the holder and spindle have reliable contact on the conical surface and the end, thus reducing the connection stiffness. In the process of high-speed machining, elastic deformation occurs in partial contact surface under the huge centrifugal force. Because of different deformations, the mating surface appears clearance. The contact stress and stiffness vary accordingly.

(3) Chatter caused by imbalance

When the matching surface is unbalanced as a result of wear, it results in the motorized spindle vibration, which reduces the machining accuracy, accelerates the wear and tear of the front and rear bearings of the motorized spindle, and causes machining chatter.

3 Degraded features extraction

Under fixed working condition, when the mating surface deteriorates, the cutting power and torque will vary. Meanwhile, the features of the current will be different. Monitoring current signal does not disturb the machining process, and can avoid the interference of coolant, chips and vibration in the cutting environment.

3.1 Wavelet packet denoising with adaptive Threshold

The spindle current in high speed machining is complex and changeable, with dynamic and non-linear characteristics. Wavelet analysis and wavelet packet analysis are suitable for non-stationary signal processing. Compared with wavelet analysis, wavelet packet decomposition is more precise [25]. The signal is decomposed by n-layer wavelet packet and then the decomposed wavelet packet coefficients are denoised according to the threshold function shown in Equation (2). It can overcome the discontinuity of hard threshold function and reduce the constant deviation of soft threshold function [.

$$\eta(x,\lambda)=\begin{cases} x-0.4\dfrac{(\mathrm{sgn}(x)\lambda)^{a}m}{x^{a-1}}+\mathrm{sgn}(x)(k-1)\lambda & |x|\geq\lambda \\ 0.4\dfrac{m|x|^{b}}{\lambda^{b-1}}\mathrm{sgn}(x) & |x|\leq\lambda \end{cases} \tag{2}$$

where, a,b are used to change the rule of threshold function. m determines the approximation degree of wavelet threshold. λ is determined by $\sigma\sqrt{2\log(N)}$,where σ is the standard deviation of noise signal and N is the length of signal[26].

3.2 Wavelet packet entropy extraction

Shannon entropy in information entropy theories has strong anti-jamming ability. Its combination with denoising wavelet packet coefficients can accurately characterize the performance changes. The denoising wavelet packet coefficients are S_{nk} , where: $k=0,1,2,...,2^{n}-1$, n is the number of decomposition layer, from which the energy of the wavelet packet can be obtained, as Equation (3).

$$E_{nk}=\sum_{k=0}^{m}|S_{nk}|^{2}\ \ (m=2^{n}-1) \tag{3}$$

The energy of sub-node coefficients is normalized as follow:

$$e_{n,k}=\frac{E_{n,k}}{\sum_{k=0}^{m}E_{n,k}} \tag{4}$$

where, e_{nk} is the probability of the information energy contained in the k sub-band in the total energy. According to the basic theory of Shannon information entropy, the nth wavelet packet entropy $H_{n,k}$ is defined as:

$$H_{n,k}=-\sum_{i=0}^{m}e_{n,k}\log e_{n,k} \tag{5}$$

Feature signals from degradation to failure are collected at the predetermined times $x_i, i=1,2,...,i$. After denoised by wavelet packet, their wavelet packets entropy is denoted as $y_i, i=1,2,...,i$.

4 A hybrid prognostics model framework

After the array $[x_i, y_i]$ is trained by RVM, the sparse vectors $y_r^{*}=\{y_1^{*}, y_2^{*},..., y_r^{*}\}$ are extracted at the corresponding time $x_r^{*}=\{x_1^{*}, x_2^{*},..., x_r^{*}\}$. $[x_r^{*}, y_r^{*}]$ is relevance vectors(RVs) set, where r is much less than i [27]. Then, the parameters of the power regression (statistical model) proposed in this paper are calculated by fitting sparse array $[x_r^{*}, t_r^{*}]$. Finally, the fitted model is extrapolated to failure threshold for RUL prediction. Fig.3 presents a flowchart to detail the data processing process from signal acquuired to RUL prediction.

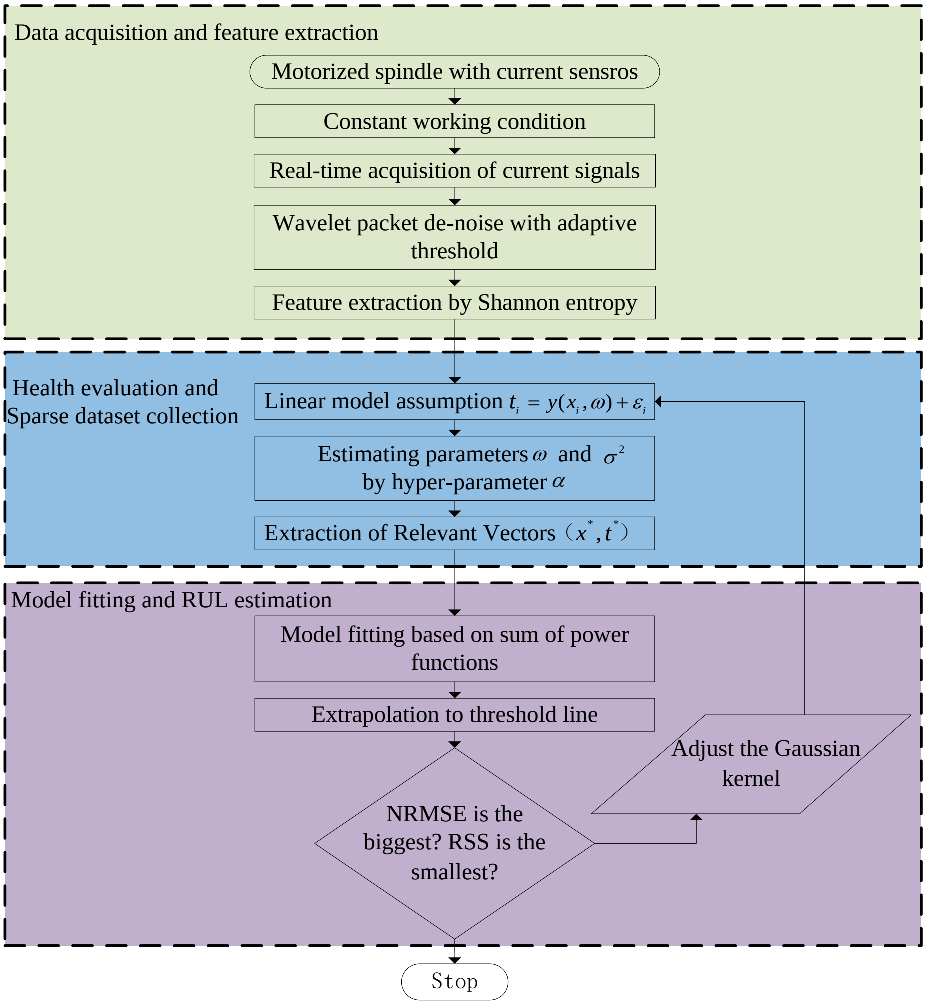

Fig.3. Flowchart of the RUL prediction

4.1 Fitting function model

The sum of power functions is used to fit the degradation performance curve, which is given by:

$$y_i = a.x_i^b + c.x_i^d, i = 1, 2, ..., r \tag{6}$$

where, the coefficients a, b, c and d are solved according to the RVs $(x_i^*, y_i^*), i = 1, 2, ...r$

The fitting curve is extrapolated to the threshold line. The predicted RUL is $\hat{RUL}$ [28,29,30]. The prediction accuracy of RUL can be evaluated by RA.

$$RA = \left[1 - \frac{\left| RUL - \hat{RUL} \right|}{RUL} \right] \times 100\% \tag{7}$$

where, RUL is the actual remaining useful life and $\hat{RUL}$ is the predicted one.

4.2 Evaluation of fitting performance

1. Normalized Root Mean Squared Error (NRMSE)

$$NRMSE = 1 - \frac{\left\| \hat{y}_i - y_i \right\|}{\left\| \hat{y}_i - \sum_{i=1}^{n} \hat{y}_i \right\|} \tag{8}$$

2. Residual Sum of Squares (RSS)

$$RSS = \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \tag{9}$$

In Equation (8) and Equation (9), $\hat{y}_i$ is the predicted value. y_i is the true value. n is the number of fitting points.

5 Test validation

The life test of the spindle-tool holder was carried out on the spindle test platform as shown in Fig. 4. In order to simulate the actual working conditions, the hydraulic driving device is used to exert force on the spindle-tool holder, and the dynamometer is used to load the torque. The type of the motorized spindle is NAEVF-20A-08-E with HSK tool holder. The model of AC transmitter is HKT-4I-0.5，which is used to monitor three-phase AC of spindle .

5.1 The specified test conditions

In the experiment, the speed of the spindle was 1000 rpm with 1.2kN.m torque. Monitoring spindle current with AC transmitter lasted for 14 months throughout the life cycle. The sampling frequency is 5012Hz.

Two hundred sets of wavelet packet entropy values were extracted at different stages, of which one hundred sets were used as training data and another one hundred sets were used as test data.

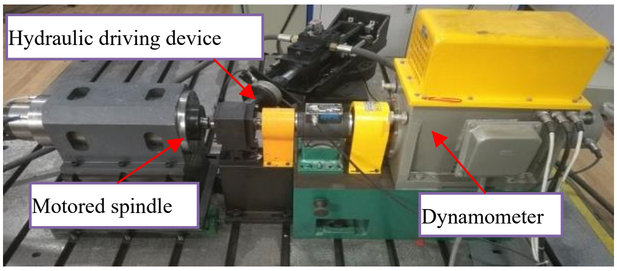

Fig.4. Motorized spindle platform

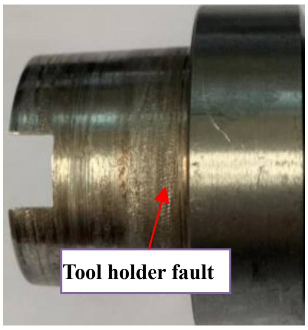

Fig .5. HSK tool holder after test

5.2 Feature extraction and RUL prediction

Each set of the spindle current was decomposed into three-layer wavelet packets, with the db4 wavelet function. The third-level wavelet packet coefficients were denoised by using the threshold function in Equation 2.

The wavelet packet entropy of each set is calculated with denoising node coefficients.

The RBF kernel function was used to train the RVM, as shown in Equation (10).

$$K(x, y) = \exp\left(-\frac{\left\| x - y \right\|^2}{\delta^2} \right) \tag{10}$$

where δ is the width of the kernel function, and its optimal value is searched from 20 to 100 with the step 0.2.

In order to verify the relationship between the prediction accuracy of the proposed model and the cumulative amount of state data, three stages of data are selected for verification in the early, mid and final stages, corresponding to the number of data files in the three stages are 32, 62, 72, respectively.

The first 32 sets of training data were selected for RVM model training, and the corresponding RVs are these circles in Fig.6. In order to recognize and judge the running state of spindle-tool holder effectively, corresponding 32 sets of test data were used to evaluate the present health state. The prediction curve obtained by RVM is shown in Fig. 6 with the label "prediction curve by RVM".

According to the sum of power functions shown in Equation 6, the coefficients a,b,c,d were solved according to the set of RVs. The predicted curve is extrapolated to the failure threshold curve with the intersection point T_i .The predicted residual life is $\hat{RUL}(x_j)=T_i-x_j$, where x_j is the data set serial number.

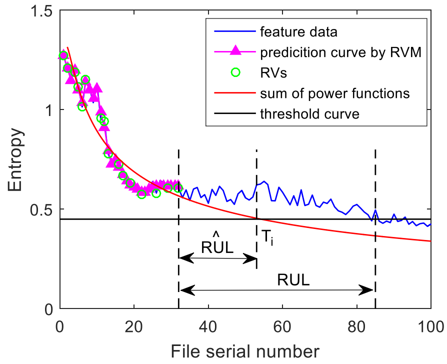

Fig .6. RVM-sum of power function with 32 sets of data

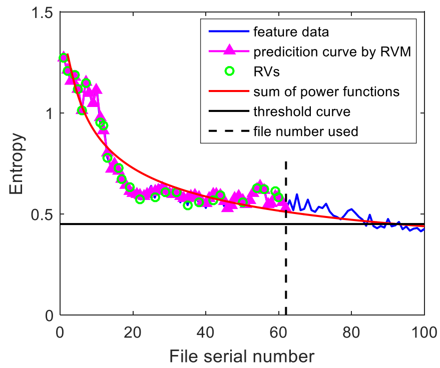

Fig.7. RVM-sum of power function with 62 sets of data

Similarly, the first 62 and 72 sets of test data were estimated, and the RUL was predicted, as shown in Fig.7 and Fig.8. The RUL prediction accuracy based on RVM-sum of power functions is shown in Table 1.

Table 1. Prediction accuracy based on RVM –sum of power functions

File number	RUL	$\hat{RUL}$	RA
32	58	22.15	38.2%
62	28	30.5	91.07%
72	18	23.82	67.7%

It reveals that the prediction accuracy of 62 sets data is the highest. For the prediction of 32 sets of data, because of the small amount of RVs, it can't reflect the overall degradation trend, so the accuracy is the lowest. For 72 sets of data, the fitting performance of the curve is better due to the increase of the number of RVs, However, the prediction accuracy of residual life is reduced. It is necessary to adjust the Gaussian kernel and reselect the RVs for fitting curve.

5.3 Comparative analysis of fitting performance

The RVM-sum of power functions prediction model is compared with RVM-single power function and feature data-sum of power function, as shown in Table 2, where the feature data is the wavelet packet entropy value.

Table 2. Performance comparison of three fitting model

Fitting function	File number	NRMSE	RSS
RVM-sum of power functions	32	0.7067	0.0754
	62	0.6761	0.1424
	72	0.6181	0.1443
RVM-single power function	32	0.6354	0.2055
	62	0.6203	0.3565
	72	0.6180	0.3906
Initial data-sum of power functions	32	0.4699	0.2055
	62	0.5664	0.2443
	72	0.5758	0.2244

RVM-single power function fitting is shown in Fig.9, with corresponding single power function $y_{\rm i} = a.x_i^b, i = 1,2,...,r$. Feature data-sum of power function combination power is shown in Fig. 10.

Table 2 indicates that NRMSE of the RVM-sum of power function model is higher than those of the other two models, while the RSS is lower than those of the other two models. It can be concluded that the RUL prediction model proposed in this paper can accurately fit the degradation curve.

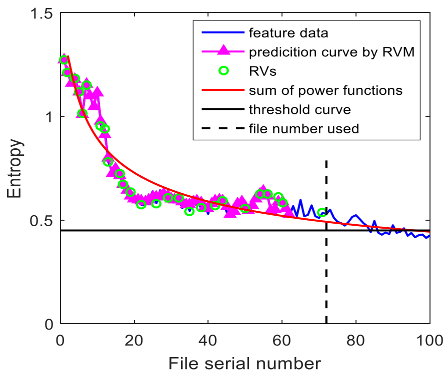

Fig.8. RVM-sum of power function with72 sets of data

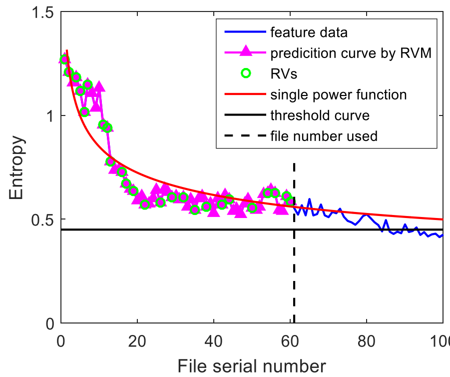

Fig.9. RVM-single power function with62 sets of data

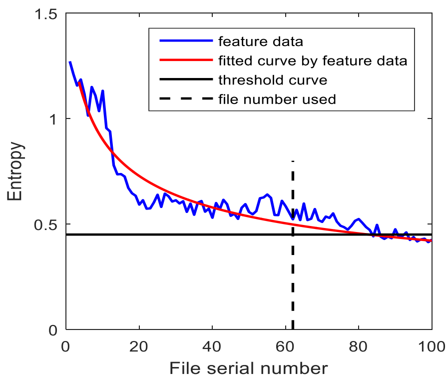

Fig.10. Feature data-sum of power function with62 sets of data

6 Conclusions

1. In order to estimate and predict the state performance of the motorized spindle-tool holder, a mapping model between the degradation characteristics of the motorized spindle-tool holder and the current was proposed. At the same time, the failure mechanism of HSK tool holder was emphatically analyzed.

2. After adaptive threshold denoising, wavelet packet entropy was proposed to characterize the degradation of spindle-tool holder performance. Experiments verify that the signal processing technique can reflect the degradation trend obviously.

3. A hybrid approach is presented, Utilizing the advantages of AI-model and statistical-based model. The RVM- sum of power function is constructed, and its fitting effect has obvious advantages over the other two schemes. This model is suitable for high reliability equipment with scarce failure degraded data. The results of RUL prediction can provide an effective reference for preventive maintenance and spare parts management.

4. The failure threshold of motorized spindle-tool holder needs to be further studied according to the actual processing accuracy requirements and machining conditions.

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Conflicts of Interest: The authors declare no conflict of interest.

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